Pairs Trading Efficiency in European Markets

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Biographical Summary

Pedro Lourenço dos Santos was born on the 13th of January of 1992 in Porto, Portugal. Pedro was always a good student in school, conciliating the best grades with his interest sports which was visible in his participation in many tennis tournaments and his loyal support to Boavista Futebol Clube. Since young ages, Pedro was interested is understanding how businesses worked and had curiosity in the prices of different products and services. He had no doubts in choosing socioeconomic sciences area for high school studies, which concluded in 2010 with very good grades, both in his college disciplines and in the final national exams of economics and mathematics.

In 2013, Pedro finished the bachelor degree in economics from Faculdade de Economia da Universidade do Porto (FEP). During his bachelor experience, Pedro did Erasmus for six months in Bucharest and was part of a traditional academic student music group called Tuna Académica da Faculdade de Economia do Porto (TAFEP). These two experiences contributed for Pedro developing social skills besides the technical skills acquired during his studies.

Pedro decided to pursue studies and enrolled in the Master in Finance also from FEP. He joined a student club, called FEP Finance Club, where he performed activities related with financial markets and did two business trips to London and Madrid. In the beginning of the second year of the Master in Finance, Pedro started his professional career with an internship of three months in the transaction advisory services team at Ernst & Young S.A. in his city, which was followed by a six-month internship at BNP Paribas Arbitrage in Paris where he had collaborated with the structured equity team.

In July 2015, Pedro moved to Lisbon and worked one year with the equity sales trading team from Millennium Investment Bank. It was during this work experience, and while trying to find the best investment options for his clients, in an extreme volatile moment in financial markets, that Pedro had gained motivation to do a thesis on pairs trading. Since March 2017, Pedro is working in the asset management team of BPI Suisse in Geneva.

Acknowledgments

First, I would like to thank all my family for all the education they gave me and for having supported me in every step of my life. It is mainly because of them that I am who I am and I had the opportunity to realize this master. Primarily, my grandparents are the greatest inspiration for me since they had to work hard and passed many obstacles in order to give a better future for their sons. I thank also my parents for always trying to suggest the best paths for my life with a great sense of flexibility. Finally, my sister, who completed last year a PhD and is a great inspiration for me.

Second, I have to thank all my friends not only for all the constant motivation they gave me in order to finish this thesis, but also for all the support in the good and bad moments along with the leisure moments which are very important for a balanced life and my well-being.

Third, I thank all the teachers and staff from Faculdade de Economia da Universidade do Porto (FEP), and in particular the director of the Master's in Finance program professor Paulo Pereira, for all the learning I had during the last years. More recently, I am also grateful to all my colleagues with whom I have interacted during my working experiences, as I am constantly learning and the inspiration for my work comes from all these experiences.

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Abstract

This dissertation studies the performance of a simple pairs trading strategy in four European indexes, namely the PSI 20 Index, IBEX 35 Index, CAC 40 Index and DAX 30 Index, between 2006 and 2016. The resilience of the pairs trading strategy is challenged when the author chooses pairs based on industry group classification and then during the trading period he does not change the pairs. Other innovation from the author is the continuous update of the triggers by daily calculating the one-year average and one-year standard deviation of the spread between pairs. The results from the pairs trading strategy suggest a small but positive return during the period studied, a very low standard deviation and a small correlation with equity benchmarks.

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1. Introduction

Trying to find investment strategies with good returns potential and low risk profile is a difficult challenge who is constantly followed by investors and researchers in financial markets. In an atmosphere of low interest rates and having present the possibility of stock crashes periods, the search for alternative ways to generate profits in financial markets is of greater importance. Therefore, over the last years we observed an increase in popularity investment strategies trying to avoid market risk, usually called market-neutral investment strategies, and where pairs trading is included.

In fact, pairs trading started to be known in the mid 1980's after being employed by Nunzio Tartaglia and his quantitative team working at Morgan Stanley. First it was used as a hedging tool to offset large block trades made by Morgan Stanley's equity block trading desk operations and later pairs trades start been thought as a profit making strategy with two sides.

The idea behind pairs trading involves the use of relative pricing by looking at the historical price relationship between two securities in order to identify which one is overvalued or undervalued in relation to the other one.

The trading process behind common equity pairs trading involves buying the undervalued security and selling the overvalued security, which results in the overall return of the long-short portfolio being uncorrelated with the long only market return, offering protection in case of a market crash.

It should be noticed that the above explanation reflects the basic idea behind traditional equity pairs trading strategies, however there are different ways of implementing this type of strategy. Some variations of pairs trading strategies include the use of different financial instruments such as currencies, commodities or options, while one can use different technical or fundamental methods to evaluate the securities.

In this study, we will focus only on equity pairs trading between two securities and we will use mainly technical methods already addressed in previous literature together with innovations coming from author's ideas.

Some typical questions regarding pairs trading implementation and results are going to be accessed during this work:

1. How should one decide which securities are going to be grouped together as a pair?
2. What distance deviation between the pair should be good enough in order to initiate the trade and what distance will trigger the close of the trade?
3. Are pairs trading returns consistent and stable?
4. Can a retail investor make profits with a simple pairs trading strategy?

For the first and second questions, there is no exact answer. Previous literature on the topic suggests different methodologies and our challenge is to choose the solution which best fits the data, resources and goals of this study. Regarding the third question, some previous studies questioned pairs trading returns robustness to transaction costs while recent literature reported a decline in pairs trading returns. Finally, since this strategy is more common among hedge funds and institutional investors, our idea is to perceive if a retail investor with little resources would be also able to apply a pairs trading strategy.

Besides these interesting questions, there are other aspects of interest on this thesis. First, the fact that pairs trading is a market neutral strategy, makes it interesting to compare the results of this strategy with market returns. Second, since pairs trading is a strategy based only on past information, it will be a test for the weak-form of market efficiency if we could have regular profits. Third, although pairs trading is relatively known in the trading sphere, it did not have the same attention in academic research as other strategies. Finally, this thesis will cover the European indexes DAX 30, CAC 40, IBEX 35 and PSI 20, which are not usually covered in previous literature.

This thesis is organized as follows. In first section, we propose an explanation of the main characteristics related to the pairs trading strategy. During that chapter, important concepts such as the efficient market hypothesis are addressed, as well as the risks of investing in pairs trading. In section three, we will briefly describe the main previous literature on pairs trading. This part is important for a better understanding of our methodology, which will be fully explained in section four, including the innovations we made to the base model used in previous literature. Chapter four include also the description of the data used in this thesis.

Section 5 starts by describing some particularities associated with the calculation of pairs trading returns. Before the main results of our empirical analysis being discussed, we will also cover an explanation regarding transaction costs and the assumptions we have made for our work. To conclude this chapter, we perform a sensitivity analysis on the triggers for opening or closing a trade and we test the inclusion of a stop-loss in our model. Before the last section which is devoted for the conclusions and summary of this thesis, we addressed in chapter 6 some ideas for future research on pairs trading.

2. Pairs Trading Review

We decided to start this work with a brief explanation of the main concepts around pairs trading. First, we described some distinguishing characteristics of this type of strategy that make it appealing for investors and then we addressed the risks involved in pairs trading investing. We believed it would be the best way to start since this clarification will include important ideas from the investment world and will help readers to have a better understanding of our study.

Common trading strategies involves the use of long positions and generate positive returns whenever markets go up. On the other hand, if an investor believe markets will go down, short positions can be used to benefit from market decreases. Both strategies mentioned above are called directional trading strategies as their profits derive from the market direction. As opposed to directional trading, pairs trading is considered a market neutral investment strategy.

Market neutrality is the first important feature of pairs trading strategies and, as the name suggests, is a characteristic of strategies whose profits are independent of the direction of the markets. Considering beta as a measure of market or systematic risk, market neutral portfolios may be defined as portfolios whose beta is zero. To accomplish that result, usually market neutral strategies involve the use of long and short positions.

The second main characteristic of pairs trading strategies is the relative value proposition. Instead of trying to evaluate the absolute value of a security alone, pair traders observe the relationship between two similar securities and when the price spread between these securities deviates from his historical mean, a long position is opened in the security underperforming the other one while a short position is taken in the overperforming security.

Pairs trading is also considered a statistical arbitrage investment strategy. While the basic definition of arbitrage involves buying a security in one market and simultaneously selling it at a higher price in another market generating a profit without risk, in pairs trading the arbitrage opportunity is based on implied pricing discrepancy between two securities using a statistical model for evaluating the expected value of the price relation between the two securities.

Regarding how should be the performance of a pairs trading strategy, assuming that a sufficiently diversified portfolio so as to eliminate unsystematic risks, following the capital asset pricing model rational, which relates risk and expected return, the strategy should earn a return similar to the risk-free rate of return, which is usually associated with the return from government bonds.

Pair traders expect to earn consistently positive return regardless of market conditions, which is obtained when long positions outperform the short positions in rising markets and when the opposite occurs during falling markets. In order to achieve that return profile, pair traders believe that when the relationship between two securities has deviated from its historical average in a statistically significant way, there will be a convergence of these fluctuations back to their historical mean relationship.

Considering the efficient market hypothesis principle that securities are fairly priced in the market and that arbitrage situations cannot persist, as proposed in Fama (1970), getting excess risk adjusted returns in a systematic way with pairs trading would be a violation of this principle, so we should evaluate possible risk on pairs trading investment strategies that could justify positive performances.

Model risk refers to the ability of a model from an investor accurately predict the price movement for which it was designed. Usually models have the underlying assumption that patterns identified in the past are likely to repeat themselves in the future which may end up not being proven. The use of statistical models with computer systems and trades executed automatically increases the model risk.

Another major risk factor faced by pairs traders is execution risk. Execution risk is related with the concern that poor execution will adversely affect portfolio performance and can be driven by liquidity concerns, commissions or short sale and margin rules. Even after a trade has been placed successfully, liquidity problems may make it impossible to exit a trade and realize a gain.

Finally, security selection risk is the risk that the securities selected will experience adverse price action as the result of an outside force, usually in the form of a news report or company announcement. The higher the number of different pairs in a portfolio, the lower would be security selection risk. If two securities are highly correlated, usually the outside force would have similar effect in both securities and the combined effect and security risk would be lower compared with a long only investment in these securities.

3. Literature Review

Pairs trading is a very recent topic in literature. While this strategy started to be known in the mid 1980's after being employed at Morgan Stanley, the trading methodologies were not openly disclosed due to the proprietary nature of the field. Only in 2000's decade some studies started focusing on different ways in which the pairs trading strategy could be implemented.

The first empirical work referring to pairs trading is attributed to Gatev, Goetzman and Rouwenhorst (1998) where it was documented an analysis of this strategy and how it affects the theory about market efficiency. This work was updated in 2006 with more recent data and reporting considerable profits which were uncorrelated to the S&P 500. Gatev et al. (2006) became the most cited paper regarding pairs trading and was also the basis for our work, reason why the next paragraphs have a complete explanation of their methodology.

In the implementation of the pairs trading strategies the authors used two stages called formation period and trading period. The formation period was twelve-months long and corresponded to the period where the equity pairs were identified using the distance method. The distance method started with the normalization of all stock price series by creating a cumulative total return index for each stock and then selecting the matching partner for each stock which would be the security minimizing the sum of squared deviations between the two normalized price series.

The trading period started on the day following the last day of the pairs formation period and using only the top 5 and 20 pairs with the smallest value in the calculated historical distance measure. The trading rule was described as follows: opening a position in a pair when prices diverged by more than two historical standard deviations from the mean spread and close the position when prices crossed again. In the case there is no cross in prices before the end of the trading interval, the close of the position occurs in the last trading period day.

The reason to use this approach was because it was the best approximation of the description of how traders themselves choose pairs after their interviews with pair traders suggested that they try to find two stocks whose prices "move together". Gatev et al.

(2006) stated “In our study we have not searched over the full strategy space to identify successful trading rules, but rather we have interpreted practitioner description of pairs trading as straightforwardly as possible”.

Regarding the performance of their pairs trading strategy, it reached average annualized excess returns of 11% for the period 1962-2002 net of conservative transaction costs. They have also underlined that returns were decreasing in recent years due to an increased hedge fund activity.

Other interesting conclusion from Gatev et al. (2006) include the breakdown of the top 20 pairs by industry composition, which on average 71% of the stocks were from the utility sector and usually these stocks tend to have lower volatility. When comparing different sectors, they have concluded pairs trading was profitable in every broad sector category and not limited to a particular sector.

Some authors have suggested different methods for formulating a pairs trading strategy. Vidyamurthy (2004) proposed the cointegration approach trying to parametrize the strategy. Cointegration was initially proposed by Engle and Granger (1987) as a measure of long-term dependencies which could solve the problem of spurious regressions that suggest relationships even when there are none.

Technically, if two non-stationary time series become stationary when differenced we say these two time-series are cointegrated. Equity pairs traders can use cointegration to analyze time series from two different stocks and if they have an expected long-run equilibrium relationship they will use short-term deviations from equilibrium to bet in future corrections back to the estimated equilibrium.

In the next year, Elliot, Hoek and Malcolm (2005) used a mean-reverting Gaussian Markov chain model to test pairs trading. The relative price deviation of stock pairs is defined as the spread and modelled with Kalman filter. The model is regularly updated and calibrated with new data giving new estimations for the mean-reverting level.

In the same year, Andrade et al. (2005) followed the method proposed by Gatev et al. (2003), the same work updated in 2006, to study a pairs trading strategy in Taiwan Stock Exchange, between 1994 and 2002, which reached annual excess returns of 10.18%. They argued that known sources of systematic risk could not explain the returns achieved by the pairs trading strategy.

Two years later, Perlin (2007), examined a pairs trading on the 100 most liquid stocks from the Brazilian financial market, between the periods of 2000 and 2006, using the minimum squared distance rule. Perlin used daily, weekly and monthly price time-series to assess the performance and risk of pairs trading, concluding the highest excessive returns over a benchmark buy and hold portfolio were achieved with daily data and betas were very close to zero meaning a low correlation with the market.

In the following year, Papadakis and Wysicki (2008) added accounting information events, such us earnings announcements or analysts forecast, to the equation of a pairs trading strategy, using Gatev et al. (2006) method, in a portfolio of U.S. stock pairs between 1981 and 2006. They concluded these events were a significant factor affecting the profitability of a pairs trading strategy. After finding that accounting events were usually a trigger for pairs trades, they concluded higher returns could be achieved by waiting for an accounting information event to close a pairs position and opening positions in non-event periods instead of starting trades after accounting events.

Engelberg, Gao and Jagannathan (2009) performed a study with similar ideas from Papadakis and Wysicki (2008) adding informational events and general news to the accounting ones already addressed. Their analysis showed differences in the speed at which new information is incorporated in different stocks can justify increased profitability in pairs trading and if news only affects one asset it would decrease the profitability of pairs trading. Moreover, the faster convergence in prices on pairs with reduced liquidity could indicate the exposure to liquidity risk to be a justification for some excess returns.

Other widely cited study on pairs trading following Gatev et al. (2006) methodology was issued in 2010. Do and Faff (2010) concluded a pairs trading strategy with U.S. stocks have been decreasing its performance in recent years. While between 1962-1988 profits were 1.24% per each 6-month period, between 2003 and 2008 the 6-month profits were 0.6%.

One year later, the same authors tested if the returns of their pairs trading strategy were robust to trading costs such as commissions and fees. Do and Faff (2011) reported the profitability of the strategy in the U.S. equity market between 1963 and 2009 were around 30 basis points per month, while after 2002 the strategy becomes unprofitable.

Almeida (2011) used the methodology from Gatev et al. (2006) and a sample comprising U.S. stocks and the period between 1990 and 2011. Annualized returns form top 20 and top 100 portfolio were respectively 11.3% and 11.8% (1991-2002) while in 2003-2010 decreased to 5.6% and 9.9%. Lower returns from 2003 to 2007 could be justified by the publication of previous version of Gatev et al. (2006), while returns from 2008 to 2011 increased again with the best year from all-time series being 2008 with around 22% annualized return versus the worst year for S&P 500 with a decrease of 37%.

Almeida (2011) results also confirmed it is better to avoid pairs that trigger around abnormal volume changes in one of the assets, which assuming volume information as a good proxy from news confirm of Engelberg, Gao and Jagannathan (2009). Introducing a limit to the number of days a pair can stay open improved the performance for different number of days, with the best limit being 25 days with an annual increase in profits of 5%.

Branco (2012) applied a pairs trading strategy to the Portuguese stock market from 2002 to 2012 and compared the minimum distance method with the cointegration method. The minimum distance proved to be a market neutral strategy by rejecting the null hypothesis to present a beta of zero. The alpha achieved was 11% a year, while the sharpe ratio was 1,43. On the other side, the cointegration method could not be defined as a market neutral strategy because the beta was statistically significant at 0,135. The excess returns of this method were 12,5% and the sharpe ratio was 1,31.

Franco (2014) studied the US stock market between 1962 and 2013 and, in accordance to Gatev et al. (2006) and Do and Faff (2010), found a significant decrease in the pairs trading strategy performance in the last decades, especially in the period from Jan 2004 to Dec 2013. When considering 0,1% transaction costs both top 5 and top 20 remained profitable while for 1% transaction fees the top 5 portfolio sharpe ratio became negative while top 20 portfolio sharpe was almost null. By restricting the portfolios to the same-industry pairs the performance of the pairs trading strategy increased. Chan et al (2007) had already shown that stock correlations are higher within-industry than outside-industry.

Ribeiro (2015) applied a pairs trading strategy to stocks listed in the London Stock Exchange, in the period between 2004 and 2014. The average 6-month excess return achieved by the strategy was 15.39% and, as in other literature already mentioned, better results were achieved during the subprime crisis. After applying a liquidity restriction to the strategy, the performance decreased so it was argued studies with illiquid stocks could had results upward biased. By introducing stop losses defined in percentage and number of consecutive losing days, the results were also negatively affected meaning pairs could big deviations but still they have tendency to converge back again.

After summarizing important literature on pairs trading, it was noted that the theme is very recent in academic research and it generated great interest around the community since many studies have been appearing with different proposals and innovations to previous literature.

4. Data and Methodology

This chapter starts with the presentation of the data used in this study and proceeds with a detailed explanation of the selected methodology to create the equity pairs trading strategy.

4.1 Data description

The strategy starts with an initial screen which limits the universe of securities with possibility of being considered in the portfolio. Regarding the security type, as in most of previous research on pairs trading, the focus of this work is in equity securities, which is also the security class more appealing to retail investors. We recall that one of the goals of this study is to test if a simple pairs trading strategy could be applied by any retail investor.

Within the equity universe, we decided to use the components of the following indexes: PSI20 Index, IBEX35 Index, CAC40 Index and DAX30 Index. First, we wanted to do something different from previous studies, which are focused mainly on American stocks. The main Portuguese Index was chosen due to the author's nationality and then the main Spanish Index is the one more proximity to Portugal. Finally, the majors French Index and German Index were selected to complete the study universe with more liquid and big stocks also belonging to Eurozone. With this equity selection, we ensure we are not investing in illiquid securities who would have bigger bid-ask spreads and tend to be more volatile.

Data was extracted from Thomson Reuters Datastream with a temporal period from 30-12-1999 until 30-06-2016, giving 16,5 years of data series and a total number of 123 stocks. The complete initial equity universe can be seen in annex 1 in the end of this work. In order to assemble pairs from the 123 stocks screened, we have started adjusting the price series by excluding days in which the exchanges were closed (for example Christmas or other holidays in each country) so that each stock had the same time series size and there were no gaps inside the time series.

It should be noted that the price series extracted from Thomson Reuters Datastream already accounted for transactions such as stock splits and dividends. We ended up with

4152 remaining days of data and then we have eliminated 34 stocks which did not had prices for all the time series. Our final universe was therefore composed by 89 stocks. Despite the number of stocks could seem low, Alexander et al. (2002) had shown that efficient long short hedge strategies can be achieved with relatively few stocks and there were already made successful studies on pairs trading with fewer number of securities.

4.2 Methodology explanation

The minimum distance method proposed by Gatev et al. (2006) is the basis of this work. We will introduce some innovation to the model in order to include our personal beliefs and in order to fit the goals of the study. We believe based on the literature research made that the minimum distance method, besides more effective when compared with others methods addressed, has proven to be relatively simple and closer to reality.

Regarding the pairs formation, we have seen that previous literature regarding pairs trading mainly focused in looking for the closest pairs in the past and expecting that they were the ones with the highest probability of convergence after a divergence period. However, there are other forms of ranking which could be used in order to account the probability of a pair converging to a mean level not only based on the stability of the price relation.

We will use an initial criterion with the obligation of stocks belonging to the same industry classification in order to be grouped in a pair. This criteria for the creation of pairs of stocks was already studied and have shown positive results. We believed stocks with the same industry classification are considered closer to natural substitutes and in theory as one stock becomes more expensive rational investors would switch to the other stock bringing them into an equilibrium, assuming other factors remain constant.

By having a pairs formation method not only based on purely statistical inputs and including a sector restriction improves the rational of our strategy and at the same time reduces the strategy risk. If we assumed stocks belonging to the same industry group have closer betas, we would be closer to ensure market neutrality by buying equal amounts on long and short positions.

As a result, the classification "Industry Group" from Thomson Reuters Datastream to group the stocks. The 89 stocks were divided by 45 different industry groups and only 22 stocks were alone in their classification. Annex 2 in the end of this work shows the final universe of 89 stocks and their division by industry groups.

For the other 23 industry group classification which had at least two different stocks, we have studied the closeness measure (equation 4.1), similarly to the minimum distance method by Gatev et al. (2006), between stocks belonging to same industry group. We have decided to use a trigger value of 100 for the closeness value.

$$Closeness^{ab} = \sum_{i=1}^{n} \left(\frac{Pa\ i+1}{Pa\ i} - \frac{Pb\ i+1}{Pb\ i}\right)^2 \tag{4.1}$$

Therefore, two stocks will only be paired if they belong to the same industry group and the closeness measure value between 30-12-1999 and 30-12-2006 is below 100. Since our trading period will last nine and a half years, we have decided to use also a long formation period, in this case seven years.

Moreover, we used a rule to limit each stock to have only one pair, even if a stock had a closeness measure value below 100 with more than one stock in the same industry group. This rule was created in order to not be excessively exposed to one stock and to decrease the impact if any specific shock in one stock occurs. It is important to remember that the ultimate goal of market neutral investing is to reduce investment risks.

Table 1 - ***Example of Closeness study for the 10 stocks in banks industry group***

For the banks industry group, we end up with 4 different pairs. SAN paired with DBK, BNP paired with GLE, BPI paired with BKT and BCP paired with CBK. BBVA was not paired with POP because the closeness measure value between them was above 100 or in this case 379.

Closeness from 30-12-1999 until 30-12-2006										
Banks	**BCP**	**BPI**	**BBVA**	**BKT**	**POP**	**SAN**	**BNP**	**GLE**	**DBK**	**CBK**
BCP	-									34
BPI	121	-		22						
BBVA	149	53	-		379					
BKT	90	22	57	-						
POP	956	522	379	597	-					
SAN	115	21	12	29	442	-			7	
BNP	467	196	101	236	104	136	-	22		
GLE	649	303	185	358	62	235	22	-		
DBK	105	33	12	41	459	7	144	246	-	
CBK	34	114	188	79	1048	135	524	701	137	-

After doing this same analysis in all the remaining 22 industry groups, we end up with 14 pairs from 10 different industry groups to begin the trading period. It will be possible to check the stocks belonging to the 14 pairs in the section we are going to present the results. For now, we concluded the formation period stage of this work.

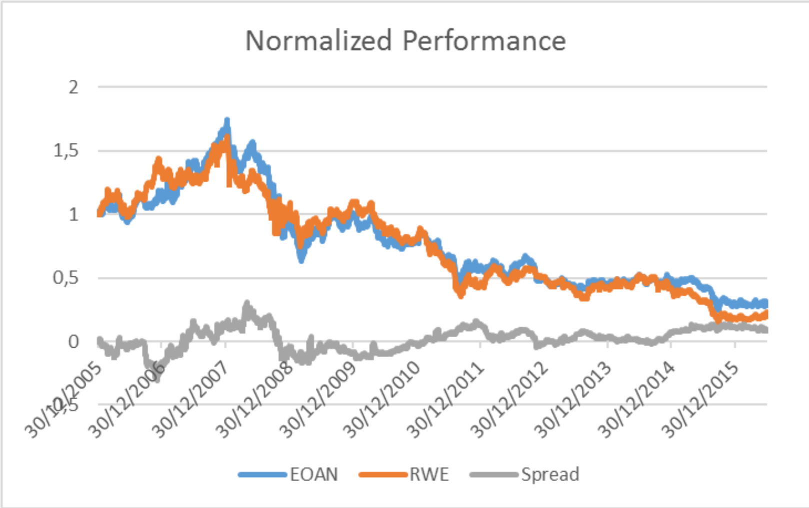
Regarding the trading period rules, as Gatev et all. (2006) reported, their method had some limitations and it was a sensible rule towards the end of a trading interval. Since, they open pairs at any point during the trading period but have to close all the pairs opened in the last day of the period, supposing a divergence occurred at the next to last day of the trading interval, this position will be opened just for one day, whatever the movement in the last day of the trading interval was.

We believe the situation reported above should not occur and we also believe in real life investors should be always following the variations in their investments and be able to adjust their positions without being constraint to act in specific time periods. The rules of our model are therefore constructed in order to overcome this issue and make the strategy more flexible and adaptive to the daily evolution of stocks covered, as every day the triggers to execute trades will be re-calculated and the trading period lasts until the last day available without any interruptions

First, we created a new time series set by the difference between the normalized prices of each security. We will call this difference the spread between the pair. For future explanations, we will call the stocks: stock A and stock B. The spread is positive if stock A had a better performance than stock B. The following Figure 1 shows an example for a better understanding of the normalized time series and the spread.

*Figure 1 – **Normalized performance and spread for the pair EOAN and RWE***

The figure below proves the stability between stock price variations from the German utilities companies EON SE and RWE AG. Due to this strong relation, the spread is close to zero during all the trading period. In an initial phase, the spread is negative because stock A (EOAN) underperformed stock B (RWE) and in the last year the spread is positive since EOAN is having a better performance than RWE.



Then, in each day we calculate the average (μ) and the standard deviation (StDev) of the spread during the last 254 days, which is the number of days used in this study as the basis for 1 year, after the adjustments of data made.

Our triggers to open a position are defined as follows:

$$\text{Spread} > \mu + 2 * \text{StDev} \tag{4.2}$$

$$\text{Spread} < \mu - 2 * \text{StDev} \tag{4.3}$$

If situation in equation 4.2 occurs, when the spread between the stocks is higher than the average plus two historical standard deviations, we will call it "Trigger 2" and will open a short position in stock A and a long position in stock B.

If situation in equation 4.3 occurs, when the spread is lower than the average minus two historical standard deviations, we will call it "Trigger -2" and will open a long position in stock A and a short position in stock B.

We defined also the triggers for closing the open positions as follows:

$$\text{Spread} < \mu + \text{StDev} \tag{4.4}$$

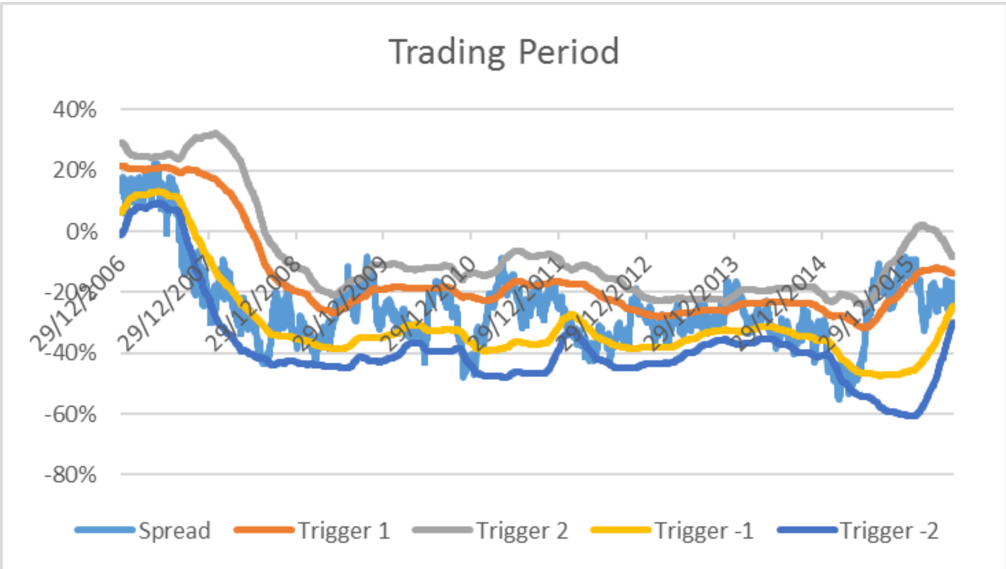
$$\text{Spread} > \mu - \text{StDev} \tag{4.5}$$

If situation in equation 4.4 occurs, when the spread between the stocks is lower than the average plus one historical standard deviation, we will call it “Trigger 1” and close the short position in stock A and the long position in stock B

If situation in equation 4.5 occurs, when the spread between the stocks is higher than the average minus one historical standard deviation, we will call it “Trigger -1” and close the long position in stock A and the short position in stock B

*Figure 2 – **Example of the trading period for the pair MEL and AC***

We can see in this figure the daily oscillation of the spread and the four triggers for Melia Hotels and Accor Hotels. For the period analyzed there were 18 trades initiated and concluded. The first one was opened and closed in the same month, June 2007, and was a long position in stock A (MEL) since the spread was below the average value. The last trade was initiated in July 2015 and closed in October 2005 and was a short position in stock A (MEL) because the spread was above the average value.



The statistical model is followed automatically and the advantage of this type of trading is that it eliminates human emotion from the trading equation which is believed to cause the failure among the investment community.

Explanations regarding returns calculations and other assumptions will be given in the next section.

5. Empirical Results

This chapter starts with explanations of important considerations regarding how to calculate returns for this type of strategies and it also includes the main assumptions for calculating the returns of the strategy here being applied.

5.1 Considerations in calculating pairs trading returns

There are some particularities regarding the calculation of pairs trading returns can have a big impact in the results of strategies like these. Long-short strategies usually have the intention of being a self-financed trade by yielding an initial net position of zero. However, it is impossible to calculate rate of returns considering a zero net capital investment. In previous literature, there are examples of the return being calculated on the long positions, on the margin capital needed for short trades, or on the gross capital exposure.

Besides the question on the amount of capital exposure, there are also issues concerning weighting schemes. Gatev et al. (2006) used two different weighting schemes. The first weighting scheme is called the committed capital scheme, which essentially commits equal amounts of capital to each one of the pairs. If the pair is not opened or it is closed during the trading period, the capital is still committed to the pair. In their second approach, they have used a fully invested weighting scheme. The fully invested scheme is less conservative as it assumes capital is always divided between the pairs that are open.

5.2 Transaction Costs

There are explicit costs and implicit costs associated with pairs trading strategies. Explicit costs include brokerage commissions and short selling costs. While brokerage commissions are the fees paid to the intermediary agent, short selling costs comes from the investor selling a stock he does not own and therefore he has to borrow it which has a cost.

The implicit costs are the bid-ask spread, which is the quantity by which the ask price is exceeding the bid price. This cost is very difficult to measure and has a great presence on this specific strategy.

Other financial limitation for this type of strategy is the extra margin an investor needs, usually around 50% of the investment, in order to enter a short position in a security.

After all these considerations regarding possible costs affecting pairs trading, we will explain our assumptions.

5.3 Assumptions

Now we are going to explain the methods and assumptions we have used to calculate the returns of our strategy. Being aware that the assumptions had an impact in the profitability of our strategy, it is important to acknowledge that the methods favored in this research were all chosen with the idea of best serving the goals of the study knowing also the restrictions of resources available. We can state that we are very satisfied with the methods used and the results achieved.

First of all, all the transactions costs were assumed as being zero as they are very difficult to quantify. Then, the prices used in this study were all end of the day prices. We know that in real life a manager may use intraday prices to observe the triggers and execute trades. With the intention of creating a model possible to work with low computing power, we use only end of the day prices.

Regarding capital exposure, we will be using the more conservative approach and mainly used in literature, which is the gross capital exposure, while with respect to the weighting scheme, we will divide the unweighted sum of returns by the total number of pairs, in our case they are 14, so we are using the more conservative committed capital weighting scheme instead of the fully invested one. During the trading period, we will adapt our exposure after each trade and if we had a profit we will reinvest them, while if we have lost money our exposure is reduced for the next trade.

Finally, we do not assume a risk-free rate of return for non-open pairs as some previous literature do. We assume zero return for the sake of cautiousness. The choice of all the above conservative approaches possibly can offset the zero transaction costs considered in this thesis.

After approaching all these different details that can have big impacts in the results, we can say that we cannot compare previous results to ours, not only because previous studies focused on US markets and covered a different time period, but also because methodologies and assumptions differ from one research to another.

To finalize this section, we will show the main formulas we use during trading period.

To calculate the returns for each trade of a pair, we use the following equation:

$$Return^{AB} = \frac{Return\ Long\ Position + Return\ Short\ Position}{2} \tag{5.1}$$

Where the returns of the long and short positions are calculated as follows:

$$Return^{LP} = \frac{Close\ Price - Open\ Price}{Open\ Price} \tag{5.2}$$

$$Return^{SP} = \frac{Open\ Price - Close\ Price}{Open\ Price} \tag{5.3}$$

Finally, we give an example of how it is computed the value of our portfolio, which starts with a value equal to one, and after the "n" trade is finished by one of the 14 pairs:

$$Value^{PTn} = Value^{PTn-1} \times (1 + \frac{Return^{ABn}}{14}) \tag{5.4}$$

5.4 Main Results

In this section, we are going to show the results and conclusions for our base scenario described above.

Table 2 – ***Summary of results from the 14 pairs***

We can see below that from the 14 pairs traded, 8 ended up with a positive return, while 6 ended up with a negative return. The number of trades was registered between 11 and 24, so we can say there were on average two trades in each year. The most important conclusion is the fact that overall there were much more positive trades then negative ones, however the magnitude of the worst trade was almost always bigger than the magnitude of the best trade, meaning that some few very bad trades drove the performances of some pairs down.

Results from 30-12-2005 until 30-06-2016							
Pair Number	1	2	3	4	5	6	7
Stocks	DBK + SAN	GLE + BNP	BPI + BKT	BCP + CBK	EGL + ANA	DG + ACS	BMW + UG
Industry Group	Banks	Banks	Banks	Banks	Construction	Construction	Automobiles
Total Returns	-17,57%	56,97%	-32,95%	4,17%	-67,34%	-6,95%	40,73%
Annualized Returns	-2,01%	4,86%	-4,12%	0,43%	-11,11%	-0,76%	3,66%
Number of Trades	14	21	18	13	17	16	20
Positive Trades	10	18	9	8	13	11	14
Negatives Trades	4	3	9	5	4	5	6
Best Trade	8,26%	14,73%	12,40%	12,79%	22,80%	4,29%	13,73%
Worst Trade	-30,31%	-10,62%	-25,85%	-12,17%	-69,59%	-15,32%	-18,14%

Results from 30-12-2005 until 30-06-2016							
Pair Number	8	9	10	11	12	13	14
Stocks	NOS + VIV	PHR + TEF	ALV + CS	JMT + SON	BAS + LIN	EOAN + RWE	MEL + AC
Industry Group	Broadcast	Telecom	Insurance	Food Retail	Chemicals	Multiutilities	Hotels
Total Returns	40,94%	-15,29%	27,79%	-18,43%	63,04%	0,38%	66,90%
Annualized Returns	3,68%	-1,73%	2,61%	-2,12%	5,28%	0,04%	5,54%
Number of Trades	16	16	17	24	21	11	18
Positive Trades	12	11	13	15	20	7	16
Negatives Trades	4	4	4	9	1	4	2
Best Trade	6,65%	26,32%	5,61%	5,02%	5,89%	4,93%	11,99%
Worst Trade	-6,17%	-46,70%	-3,09%	-14,58%	-0,28%	-6,15%	-7,68%

*Table 3 – **6-month performance pairs trading strategy vs benchmarks***

From the top of the table we can observe that over the last 9.5 years our pairs trading strategy delivered annually 1.09 % positive returns. Note that from the four European indexes in comparison, only the German one performed positively in the same period. Our strategy had definitively the lowest standard deviation when compared with the equity benchmarks, which was expected from a long short strategy. We can see from the amplitude of variations in the half years that the pairs trading strategy is not affected by big recessions such as the year 2008. Nevertheless, it does not benefit as well in the periods when the European indexes were expanding more such as the 2nd half of 2009, 2nd half of 2012 or 2nd half of 2013.

Total Returns	**10,81%**	**-60,23%**	**-42,29%**	**-23,54%**	**46,74%**
Annualized Returns	**1,09%**	**-9,25%**	**-5,62%**	**-2,79%**	**4,12%**
Standard Deviation	**2,58%**	**18,12%**	**15,18%**	**13,74%**	**14,32%**
Period	**Pairs Trading Strategy**	**PSI 20**	**IBEX 35**	**CAC 40**	**DAX 30**
1st half 2007	5,02%	19,53%	5,27%	9,26%	21,38%
2nd half 2007	1,83%	-2,59%	1,95%	-7,06%	0,75%
1st half 2008	-2,08%	-31,71%	-20,66%	-21,19%	-20,44%
2nd half 2008	3,16%	-28,60%	-23,66%	-27,46%	-25,06%
1st half 2009	0,38%	11,85%	6,44%	-2,38%	-0,03%
2nd half 2009	3,92%	19,54%	21,99%	25,32%	23,89%
1st half 2010	-0,08%	-16,88%	-22,42%	-12,52%	0,14%
2nd half 2010	1,08%	8,31%	6,43%	11,85%	15,90%
1st half 2011	0,83%	-4,30%	5,08%	3,41%	6,68%
2nd half 2011	-0,63%	-24,98%	-17,31%	-20,65%	-20,04%
1st half 2012	-2,11%	-14,49%	-17,09%	1,17%	8,78%
2nd half 2012	-1,19%	20,47%	14,49%	13,25%	18,64%
1st half 2013	2,99%	-1,81%	-4,53%	3,28%	4,56%
2nd half 2013	0,21%	17,94%	27,56%	14,36%	20,01%
1st half 2014	-5,42%	3,79%	10,32%	3,44%	2,94%
2nd half 2014	1,34%	-29,40%	-5,90%	-4,01%	-0,28%
1st half 2015	-1,17%	15,60%	4,77%	12,83%	11,62%
2nd half 2015	-1,28%	-4,22%	-10,47%	-2,36%	-1,85%
1st half 2016	4,09%	-16,25%	-15,34%	-9,40%	-9,89%

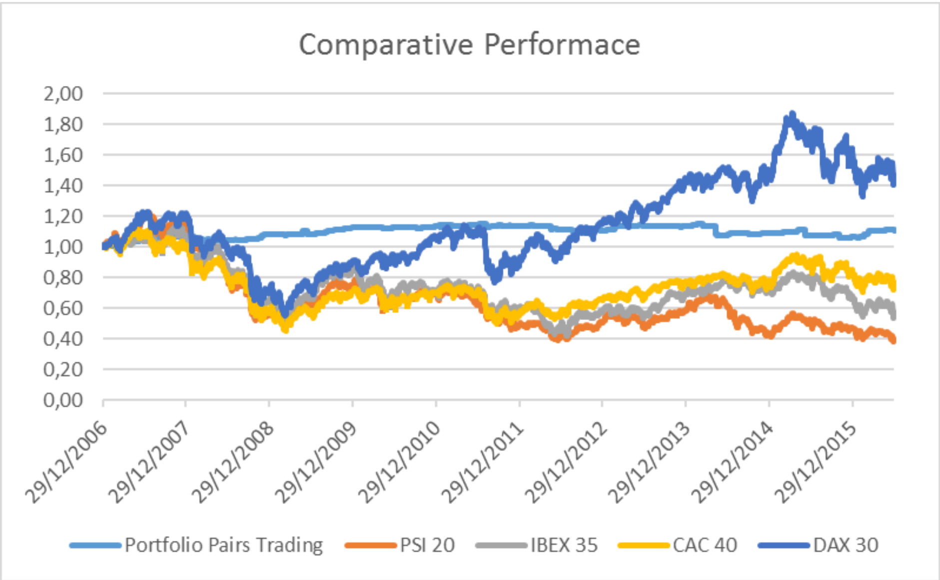
*Table 4 – **Correlation pairs trading strategy vs benchmarks***

This table shows the correlation of the returns presented in the previous table. The very low values of the pairs trading strategy confirm its tendency for being a market neutral strategy. DAX 30 and CAC 40 presented a very big correlation, despite the difference in performance, which can be attributed for some similarities in the type of company components in each index.

Correlations	Portfolio Pairs Trading	PSI 20	IBEX 35	CAC 40	DAX 30
Portfolio Pairs Trading	100,00%	8,43%	3,10%	6,88%	11,55%
PSI 20	8,43%	100,00%	86,95%	87,19%	85,66%
IBEX 35	3,10%	86,95%	100,00%	85,87%	80,40%
CAC 40	6,88%	87,19%	85,87%	100,00%	95,67%
DAX 30	11,55%	85,66%	80,40%	95,67%	100,00%

*Figure 3 – **Comparative performance pairs trading strategy vs benchmarks***

In this figure, we have clear view of the difference in terms of volatility between the pairs trading strategy and the benchmarks. We can say that the cumulative performance of the pairs trading strategy shows a regular pattern more similar to fixed income securities.



From the previous tables and figures it was possible to extract important conclusions and we could not only compare the pairs trading strategy with the equity indexes benchmarks, but we also examined how the strategy performed in different periods, including expansion and recession periods. The next phase will be to perform robustness tests for different variables.

5.5 Triggers Sensitivity Analysis

This section will test if by changing the triggers for opening and closing trades we can improve the results. We will be studying the level of divergence required for trade opening and for the close of the trade and what we are going to change is the number by which we multiply the historical standard deviations to get the triggers. The basis scenario was 2 StDev for opening the position and 1 StDev for closing the position.

*Table 5 – **Triggers Sensitivity Analysis***

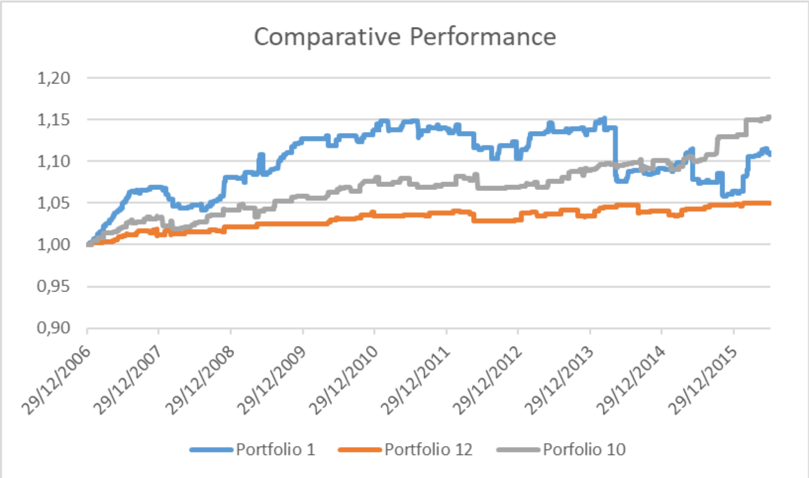
The next tables compare the base scenario corresponding to Portfolio 1, which have values of 1 and 2 for trigger 1 and trigger 2 respectively, with portfolios formed exactly the same way but modifying the trigger 1 and trigger 2 values. The solution that maximizes the return is the Portfolio 10, with a total return of 15,31% and was calculated with each trigger increased by 0,5 form the original values. Portfolio 9 also increased the base scenario total return, but has more trading activity which increases transaction costs. Finally, a solution for investors with more aversion to risk would be Portfolio 12 which delivered the minimum worst trade and also amount only a total of 80 trades during the 9,5 years.

Results from 30-12-2005 until 30-06-2016							
Strategy	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6	Portfolio 7
Trigger 1	1	1	1	1	0,5	0	0,5
Trigger 2	2	2,5	3	1,5	1,5	1,5	2
Total Returns	10,81%	8,41%	1,51%	-0,91%	4,28%	-5,64%	8,59%
Annualized Returns	1,09%	0,85%	0,16%	-0,10%	0,44%	-0,61%	0,87%
Number of Trades	242	130	71	348	282	206	199
Positive Trades	177	95	49	253	207	146	144
Negatives Trades	64	35	22	92	72	60	54
Best Trade	1,74%	1,87%	1,77%	2,42%	1,25%	2,77%	1,73%
Worst Trade	-4,97%	-4,42%	-4,13%	-5,19%	-4,33%	-7,32%	-4,14%

Results from 30-12-2005 until 30-06-2016							
Pair Number	Portfolio 1	Portfolio 8	Portfolio 9	Portfolio 10	Portfolio 11	Portfolio 12	Portfolio 13
Trigger 1	1	0	1,5	1,5	2	2	2,5
Trigger 2	2	2	2	2,5	2,5	3	3
Total Returns	10,81%	1,74%	12,46%	15,31%	10,40%	5,00%	5,69%
Annualized Returns	1,09%	0,18%	1,24%	1,51%	1,05%	0,52%	0,58%
Number of Trades	242	160	308	151	196	80	99
Positive Trades	177	113	223	110	138	53	71
Negatives Trades	64	47	84	40	57	27	28
Best Trade	1,74%	2,19%	1,30%	1,23%	0,74%	0,86%	0,57%
Worst Trade	-4,97%	-4,32%	-1,81%	-1,53%	-1,17%	-0,91%	-0,93%

*Figure 4 – **Comparative performance pairs trading portfolios***

The figure below compares three different pairs trading portfolios. Portfolio 1 is the base scenario of our work between these 3 portfolios is the one with the biggest number of trades and more volatility. Specially in 2014 we can observe a big decrease in value, due the close of a trade with a big deviation. Portfolio 12 as commented earlier would be the ideal one for an investor with more risk aversion, while Portfolio 10 shows a very good combination of high returns with low risk.



5.6 Stop-loss Analysis

The next step of our analysis was to evaluate if a stop-loss would be effective in our strategy. The level at which one sets a stop-loss can be extremely important to the success of an implied convergence strategy as it must be sufficiently tight to guarantee the ability of the manager to stay in business since if his strategy losses money consistently he will not be able to keep trading. The other concern that bears some consideration is the case in which the stop-loss level is too tight. While the manager wants to limit the amount of money he may lose on a given trade, by closing a trade, he runs the risk that convergence will begin after the trade is closed and an opportunity will have been lost.

*Table 6 – **Stop-loss Analysis***

We are confirmed by the next tables that a stop-loss can in fact improve pairs trading profits in case there are some pairs that have diverged too much at some moment. A stop-loss at -20% improves our base scenario total return from 10.81% to 15.13%. We are also confirmed that stop-losses too tight could not work as when we defined stop-losses at -15% and -10% they were not the best options in both cases studied. For portfolio 10 which already had a low loss in the worst trade, neither stop-loss trigger would be beneficial.

Results from 30-12-2005 until 30-06-2016					
Strategy	Portfolio 10	Portfolio 20	Portfolio 21	Portfolio 22	Portfolio 23
Trigger 1	1,5	1,5	1,5	1,5	1,5
Trigger 2	2,5	2,5	2,5	2,5	2,5
Stop-Loss	No	-25%	-20%	-15%	-10%
Total Returns	15,31%	12,77%	14,95%	13,63%	13,03%
Annualized Returns	1,51%	1,27%	1,48%	1,35%	1,30%
Number of Trades	151	162	170	184	210
Positive Trades	110	116	121	129	134
Negatives Trades	40	45	48	54	75
Best Trade	1,23%	1,23%	1,23%	1,23%	1,23%
Worst Trade	-1,53%	-1,19%	-0,93%	-1,23%	-0,78%

Results from 30-12-2005 until 30-06-2016					
Pair Number	Portfolio 1	Portfolio 24	Portfolio 25	Portfolio 27	Portfolio 28
Trigger 1	1	1	1	1	1
Trigger 2	2	2	2	2	2
Stop-Loss	No	-25%	-20%	-15%	-10%
Total Returns	10,81%	11,01%	15,13%	13,91%	12,85%
Annualized Returns	1,09%	1,11%	1,49%	1,38%	1,28%
Number of Trades	242	274	288	309	326
Positive Trades	177	194	201	203	196
Negatives Trades	64	79	86	105	129
Best Trade	1,74%	1,74%	1,74%	1,99%	1,74%
Worst Trade	-4,97%	-1,28%	-1,11%	-1,21%	-1,01%

Finally, we should stress that we are conscious that all the optimized values regarding the triggers and stop-loss which were achieved could only be valid for this specific study with these specific characteristics, assumptions and methods already mentioned. Therefore, other studies could find other values more suitable for the same variables.

We are happy to confirm that some modifications to the main method for trading pairs did not eliminate the main characteristics of this type of strategy, as being uncorrelated with market returns and with a low standard deviation of returns.

6. Further Research

We will now give some brief ideas for future research around the topic of pairs trading.

The first and simplest thing that could be done in further studies is to simply extend the number of securities in the European universe. Although this requires greater amount of computing power to analyze each possible combination, increasing the number of pairs could make a portfolio less risky and better balanced. Note also that by using less liquid stocks it should be necessary some measures to reduce the risk it would imply.

Other feature that would increase the complexity of one model but could be of interesting study is the inclusion of other variables for matching pairs or managing trades. The difficulty here is to find free and reliable data. One could use different technical or fundamental indicators, however for most potential pairs traders, these approaches requires more resources than the ones they will have.

One could also study a pairs trading strategy of multiple securities instead of just pairs of two stocks. One could trade a combination of two stocks against a benchmark index for example.

The inclusion of different securities types is also another issue that could be addressed in future studies. Pairs trading could be employed with futures, currencies or various options strategies, such as the use of covered call and put options. The use of options in pairs trading, while usually reserved for more sophisticated managers, can be a powerful tool for increasing returns and managing risk. We should also note the disadvantages of using options which include their complexity, less liquidity, and expenses.

The next and last chapter will conclude our analysis with a summary of all the most important findings of this work.

7. Conclusion

In this work, we have applied a simple pairs trading strategy to the stock components of the main stock indexes from Portugal, Spain, France and Germany between 2006 and 2016. From the original minimum distance method, proposed by Gatev et al. (2006), we have started by using the industry group as an initial criterion for pairing stocks, in order to have sector neutrality and some rational behind our strategy instead of just statistics.

Since we wanted an uninterrupted trading period of around 10 years, we have created a model more dynamic, which were daily adapting the triggers to new values for the 1-year average and 1-year standard deviation of the spread between the normalized price series of both stocks. The stocks were only chosen for one time, instead of being optimized every year, which was a great challenge for the success of the strategy as theoretically it would be riskier than the original one.

We were happy to observe the very low volatility of our strategy, even in periods of recession like 2008. Described as a market neutral strategy, we also confirmed that pairs trading had during the period studied a very low correlation with the European indexes addressed.

We should note that between 2006 and 2016 the PSI 20 Index, the IBEX 35 Index and the CAC 40 Index recorded falls in their performances, while our strategy delivered approximately an annual 1% return for the same period. After evaluating the trades of each pair we reached the conclusion that most of the trades were positive, but some few trades with great losses were dropping the profits from the pairs affected.

We have then decided to test if the common triggers used in previous literature were the best to apply to our situation. We discovered that by increasing a bit the triggers, we would have less trades and the profits improved. For example, instead of 2 historical deviations, we would use 2,5 historical deviations to open a trade. After that we tested strategy with the use of a stop-loss and again we had positive results, since a stop-loss at -20% improved our base scenario.

Regarding our initial motivation of evaluating while a retail investor could profit from pairs trading, we should stress that it is possible to create model to trade equity pairs with simple available data, however market participants with lower transaction costs and the facility to short securities would be better positioned to benefit from a pairs trading strategy.

We have no doubt pairs trading could be difficult to apply in reality, but we believe its specific characteristics would make it becoming increasingly spoken, especially in moments of uncertainty on financial markets as we are right now.

Further research could be conducted around pairs trading since there are still a lot questions and possible innovations in this recent and vast topic. We noted that many small particularities of pairs trading and the way one implements his strategy could make any study interesting, but at the same time it can be difficult to compare with others studies using different assumptions and methods.

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Annexes

Annex 1 – Initial equity universe divided by country and industry

Annex 1.1 – PSI 20 components

Portugal - PSI 20	18 stocks		
Sector	**1**	**2**	**3**
Paper	ALTR	SEM	NVG
Banks	BCP	BPI	MPIO
Containers & Package	COR		
Delivery Services	CTT		
Alt. Electricity	EDPR	EDP	
Integrated Oil & Gas	GALP		
Food Retail, Wholesale	JMT	SON	
Heavy Construction	EGL		
Broadcast & Entertain	NOS		
Fixed Line Telecom.	PHR		
Con. Electricity	RENE		
Specialty Finance	SONC		

Annex 1.2 – IBEX 35 components

Spain - IBEX 35	35 stocks						
Sector	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Diversified REITs	MRL						
Banks	BBVA	BKIA	BKT	POP	SAB	SAN	CABK
Oil Equip. & Services	TRE						
Gas Distribution	GAS	ENG					
Renewable Energy Eq.	GAM						
Integrated Oil & Gas	REP						
Food Retail,Wholesale	DIA						
Heavy Construction	FER	ANA	ACS				
Broadcast & Entertain	TL5						
Fixed Line Telecom.	TEF						
Con. Electricity	ELE	IBE	REE				
Food Products	VIS						
Full Line Insurance	MAP						
Mobile Telecom.	CLNX						
Iron & Steel	ACX	MTS					
Computer Services	IDR						
Apparel Retailers	ITX						
Biotechnology	GRF						
Transport Services	AENA	ABE					
Financial Admin.	AMS						
Hotels	MEL						
Airlines	IAG						

Annex 1.3 – CAC 40 components

France - CAC 40	40 stocks		
Sector	1	2	3
Retail REITs	LI	UL	
Banks	BNP	ACA	GLE
Oil Equip. & Services	TEC		
Automobiles	UG	RNO	
Multiutilities	ENGI		
Integrated Oil & Gas	FP		
Food Retail,Wholesale	CA		
Heavy Construction	EN	DG	
Broadcast & Entertain	VIV		
Fixed Line Telecom.	ORA		
Electrical Equipment	LR	SU	
Food Products	BN		
Full Line Insurance	CS		
Telecom. Equipment	NOKIA		
Iron & Steel	MT		
Computer Services	CAP		
Broadline Retailers	KER		
Pharmaceuticals	SANO		
Commodity Chemicals	AI		
Specialty Chemicals	SOLB		
Hotels	AC		
Aerospace	AIR	SAF	
Tires	ML		
Clothing & Accessory	MC		
Medical Supplies	EI		
Media Agencies	PUB		
Restaurants & Bars	SW		
Building Mat.& Fix.	SGO	LHN	
Distillers & Vintners	RI		
Auto Parts	FR		
Water	VIE		
Personal Products	OR		

Annex 1.4 – DAX 30 components

Germany - DAX 30	30 stocks		
Sector	1	2	3
Real Estate Hold, Dev	VNA		
Banks	DBK	CBK	
Delivery Services	DPW		
Automobiles	DAI	BMW	VOW3
Multiutilities	EOAN	RWE	
Divers. Industrials	SIE	TKA	
Nondur.Household Prod	HEN3		
Footwear	ADS		
Broadcast & Entertain	PSM		
Healthcare Providers	FRE	FME	
Building Mat.& Fix.	HEI		
Reinsurance	MUV2		
Full Line Insurance	ALV		
Mobile Telecom.	DTE		
Semiconductors	IFX		
Software	SAP		
Investment Services	DB1		
Pharmaceuticals	MRK		
Commodity Chemicals	LIN	BAS	
Specialty Chemicals	BAYN		
Personal Products	BEI		
Airlines	LHA		
Tires	CON		

Annex 2 – Equity universe after adjustment divided by industry group.

123 initial stocks from PSI 20, IBEX 35, CAC 40 and DAX 30 were reduced to 89 stocks, because 34 stocks did not have data since 30-12-1999. There are 45 different industries groups with 23 industries groups having at least 2 stocks.

	Sector	1	2	3	4	5	6	7	8	9	10
1	Banks	BCP	BPI	BBVA	BKT	POP	SAN	BNP	GLE	DBK	CBK
2	Heavy Construction	EGL	FER	ANA	ACS	EN	DG				
3	Automobiles	UG	RNO	DAI	BMW	VOW3					
4	Broadcast & Entertain	NOS	VIV	PSM							
5	Con. Electricity	REE	ELE	IBE							
6	Food Retail, Wholesale	CA	SON	JMT							
7	Fixed Line Telecom.	PHR	TEF	ORA							
8	Full Line Insurance	MAP	CS	ALV							
9	Commodity Chemicals	AI	LIN	BAS							
10	Multiutilities	EOAN	RWE								
11	Paper	SEM	NVG								
12	Specialty Chemicals	SOLB	BAYN								
13	Integrated Oil & Gas	FP	REP								
14	Healthcare Providers	FRE	FME								
15	Iron & Steel	ACX	MT								
16	Divers. Industrials	SIE	TKA								
17	Retail REITs	LI	UL								
18	Computer Services	IDR	CAP								
19	Food Products	VIS	BN								
20	Tires	ML	CON								
21	Pharmaceuticals	SAN	MRK								
22	Personal Products	OR	BEI								
23	Hotels	MEL	AC								
24	Mobile Telecom.	DTE									
25	Alt. Electricity	EDP									
26	Oil Equip. & Services	TEC									
27	Airlines	LHA									
28	Electrical Equipment	SU									
29	Transport Services	ABE									
30	Building Mat.& Fix.	SGO									
31	Containers & Package	COR									
32	Aerospace	SAF									
33	Auto Parts	FR									
34	Medical Supplies	EI									
35	Software	SAP									
36	Broadline Retailers	KER									
37	Clothing & Accessory	MC									
38	Distillers & Vintners	RI									
39	Media Agencies	PUB									
40	Restaurants & Bars	SW									
41	Gas Distribution	GAS									
42	Nondur.Household Prod	HEN3									
43	Footwear	ADS									
44	Building Mat.& Fix.	HEI									
45	Reinsurance	MUV2									